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#### How to cite:

Schreurs, Bieke; Teplovs, Chris; Ferguson, Rebecca; De Laat, Maarten and Buckingham Shum, Simon (2013). Visualizing social learning ties by type and topic: rationale and concept demonstrator. In: Third Conference on Learning Analytics and Knowledge (LAK 2013), 8-12 Apr 2013, Leuven, Belgium, ACM, pp. 33–37.

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Version: Accepted Manuscript

Link(s) to article on publisher's website:  
<http://dx.doi.org/doi:10.1145/2460296.2460305>

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# Visualizing Social Learning Ties by Type and Topic: Rationale and Concept Demonstrator

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## ABSTRACT

Social Learning Analytics (SLA) are designed to support students learning through social networks, and reflective practitioners engage in informal learning through a community of practice. This short paper reports work in progress to develop SLA motivated specifically by Networked Learning Theory, drawing on the related concepts and tools of Social Network Analytics and Social Capital Theory, which provide complementary perspectives onto the structure and content of such networks. We propose that SLA based on these perspectives needs to devise models and visualizations capable of showing not only the usual SNA metrics, but the *types of social tie* forged between actors, and *topic-specific subnetworks*. We describe a technical implementation demonstrating this approach, which extends the *Network Awareness Tool* by automatically populating it with data from a social learning platform *SocialLearn*. The result is the ability to visualize relationships between people who interact around the same topics.

## Categories and Subject Descriptors

K.3.1 [Computers and Education]: Computer Uses in Education  
H.5.3 [Group and Organization Interfaces] Computer-supported cooperative work

## General Terms

Design

## Keywords

Networked Learning, Social Learning Analytics, Social Network Analysis, Visualization

## 1. INTRODUCTION

An online network of learners in a formal or informal educational context, or reflective practitioners in a community of practice, can

be regarded as constituting a web of social relationships that reflects the flow of resources among them [1]. Examples include a group acquiring competence in technology use by sharing expertise, a community collectively building knowledge of its history, plus information resources necessary to deal with new situations [2].

Reflective practitioners, mentors and researchers could benefit from answers to questions such as: *Who learns from whom? What do they learn from each other? What kinds of interactions take place between people who learn together? In which directions do resources flow? How frequently do learning interactions take place? How important are these interactions to the people involved? What value do these learning interactions create?*

From a learning analytics point of view, if it is possible to design computationally tractable models of such learning networks, and render them in coherent ways, analytics could draw attention to potentially significant patterns based on the content, direction, type and strength of interpersonal interactions. To provide analytics for complex queries such as these, we need to design ‘structural signatures’ in our data models to serve as proxies, which can be detected by humans and/or machines. In this short paper, we report work in progress from combining OUNL’s research into the *Network Awareness Tool (NAT)* for visualizing professional *face-to-face* informal learning networks [3-4], with the OU’s proposal that *Social Learning Analytics* are an important class of analytic for participatory learning cultures [5].

In §2 we introduce Networked Learning theory, the paradigm motivating this work. §3 considers the steps needed to move from this to Social Learning Analytics software which satisfies the theory’s representational requirements. §4 then describes a demonstrator tool which goes beyond seeing social networks in topological terms (a well established approach), and seeks to show (i) the *topics* of interest (possibly expertise) within the community, and (ii) the *nature* of the social ties constituting the network.

## 2. NETWORKED LEARNING THEORY

Networked learning theory is an emerging perspective that is employed to understand learning by investigating how people develop and maintain a ‘web’ of social relations to support their learning. Networked learning is a form of informal learning, which involves people relying strongly on their social contacts for assistance and development [6]. Recent research has linked networked learning to an array of positive outcomes, including student performance and school improvement [7-10]. Networked

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LAK '13, April 08 - 12 2013, Leuven, Belgium  
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learning involves the use of information and communication technology (ICT) to promote collaborative or cooperative connections between learners, their tutors/instructors, and learning resources [11]. The term ‘networked learning’ was applied to higher education to refer to ways in which new communication technologies can influence teaching and learning [12-14].

As ICT drives increasingly varied forms of mediated collaboration and contact, the field of networked learning seeks to provide accounts of how learners appropriate these new tools to learn informally on and through the Internet. The field’s focus is on how learners (or learning designers) can build and cultivate social networks, seeing technology as just one (albeit critical) enabler, rather than ICT-innovation as an end in itself [1, 15].

Networked learning focuses on the *diversity of social relationships* that people develop, the *strategies* they use to maintain them and the *value* this creates for learning. Networked learning theory is closely linked to and uses methodologies of social network theory, including social network analysis [7, 15].

Social network analysis considers networks to be made up of *nodes* and *ties*. Nodes are the individual actors within a network and ties are the relationships between these actors. The impact of the structure of social networks can be studied on three levels: the positions actors have in a network (*individual dimension*), the relationships between actors in the network (*ties dimension*) and the overall network structure (*network dimension*).

While social network theory highlights the structural dimensions of learning networks, we also use social capital theory to frame social network studies from the perspective of content. Networks are always about something [6-7]. Social capital theory provides a lens through which we can examine the relational resources embedded in social ties and the ways in which actors interact to gain access to these resources [16].

The first systematic analysis of social capital was produced by Bourdieu [17], who defined the concept as the aggregate of the actual or potential resources existing within the relationships of a durable network. According to Lin [18], the common denominator of all major social capital theories can be summarized as: “The resources embedded in social relations and social structure which can be mobilised when an actor wishes to increase the likelihood of success in purposive action.” (p. 24).

A communities-of-practice perspective considers that networks, to be fruitful and active, require a shared framework of values and norms [2]. Learning within communities is a process within which both individual and collective learning goals and agendas are carefully and constantly negotiated in relation to a topic or domain that is of interest to each participant [19-20].

### 3. TRANSLATION INTO ANALYTICS

The Networked Learning position outlined above serves to define the broad set of phenomena considered to be important in designing effective informal learning, drawing on disciplinary perspectives and tools such as Social Network Analysis and Social Capital Theory. In order to translate this into a Social Learning Analytics software tool [5], there are minimally three interdependent steps: data capture, analysis and visualization.

**Data capture.** Our work on NAT has focused, to date, on face-to-face professional learning, with participants manually constructing their networks. NAT enabled them to see, literally and usually for the first time, what these networks looked like, and where new relevant colleagues might be. The transition to

Social Learning Analytics, with its focus on the appropriation of social media for learning, required the integration of NAT with an online learning platform, with the objective of generating NAT visualizations automatically from social interactions logged in the database. We selected the OU’s SocialLearn system [5, 15] as a data source, since we have complete control over the platform.

**Analysis.** It is necessary to translate the networked learning concepts such as *strength of social tie* and *social capital*, and levels of analysis such as *individual*, *ties* and *network dimensions*, into a data model whose structures have the potential to answer queries such as *In which directions do resources flow?*

**Visualization.** None of this pays off unless stakeholders can interact with the analytics that render their connected world more visible [19]. Visualizing networked learning activities can also assist strategic networked learning by helping learners to decide which networks they should join and which experts they should aim to connect with. Commonly used network visualization software includes NetDraw [21], Gephi [22], NodeXL[23], JUNG [24], Pajek[25] and several packages for R [26].

The approach taken in the design and development of the NAT plug-in for SocialLearn differed from these in two major ways. First, the software is designed to be used by participants who are not network analysis experts or researchers. Second, the conceptual framework we have requires data capture and network filtering by semantic content (topic or tag) as well as by the type of the social tie, moving beyond undifferentiated nodes and ties.

## 4. NAT PLUGIN FOR SOCIALLEARN

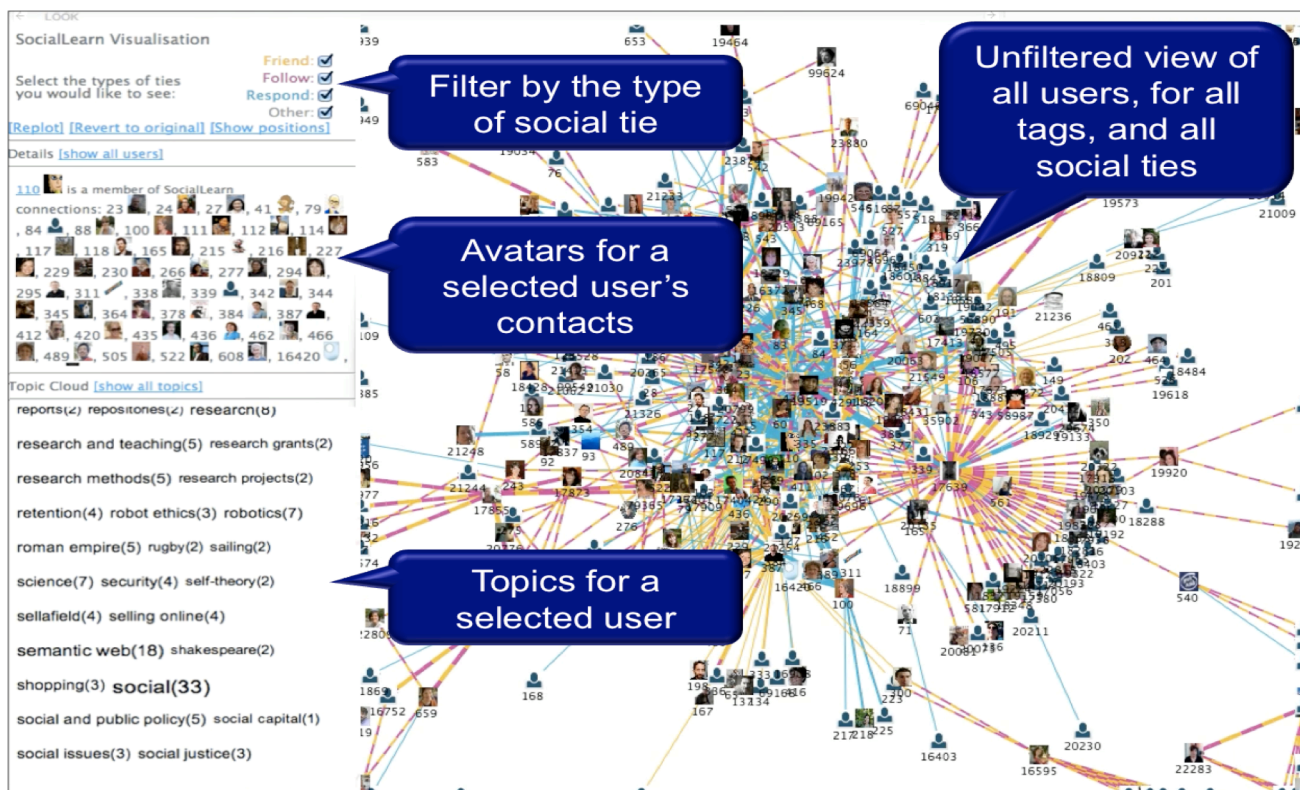
In this section we describe how we visualize multiple levels inherent in networked learning based on the learning activities within SocialLearn. The plug-in, based on the Network Awareness Tool [4], is designed to be compatible with any modern web browser and was developed using widely available JavaScript libraries. For the SocialLearn plug-in, we have set up the following framework, taking into account the theoretical perspectives introduced above.

### 4.1 Visualizing the Network Structure

The NAT plugin visualizes the overall *structure of the network* to the users. A graphical representation of the ego-network and overall network structure is visualized reflecting the current state of the network. The ego-network perspective is the network from one node. The overall network structure is the total of all nodes.

The resulting network of actors, with multiplex ties, is laid out using a force-directed layout algorithm. The resulting diagram is often complex. To reduce this complexity, users are offered a variety of ways in which they can zoom in on areas of interest, filter out extraneous data, and request details of any particular data [27]. In addition to these filters, users can request computational assistance from the system to reposition the filtered actors. In this case, the layout algorithm is re-applied to the data points of interest. A screencast demonstrating the functionality of the plug-in is online, as shown in Figure 1.

Social network theory considers that the constitution of a network may influence the accessibility of information and resources and that its social structure may offer potential for the exchange of resources [28-29]. Understanding the structure of a network can reveal the information flow within an online learning environment [30]. Teams with the same skill composition can act differently depending on the structure of relations within the team and, similarly, individual can act differently depending on their position within a network [8, 31].



**Figure 1: Using NAT to visualize and filter social ties by *person*, *type of tie*, and *topic*. Due to space limitations, this is a composite image showing the entire unfiltered network, but when a user is selected this filters the left-panel as shown, to display only her ego-network and topics. Screencast: <http://bit.ly/NAT-SocialLearn>**

To gain more insight into the tie level, we combine data about frequency and quality with the social network analysis. This supports investigation of the role of strong and weak ties in a learning network. Combining data on the frequency and the quality can be very valuable [31].

Levin and Cross [32] found that networked learners rely on weak ties with competent people they can trust. Raegans and McEvily [33] add that the transfer of tacit knowledge is a sensitive process and therefore fewer people are able to engage in this process. Strong ties are also important, because they are employed to deepen and embed knowledge that is closely related to day-to-day shared practice, as well as to build commitment to joint activities.

## 4.2 Visualizing the expertise and content

*What is the focus of the network? Which themes are discussed? Who is related to what theme? Who is at the centre of that theme?* This is represented in a tagcloud, reflecting the topics participants have declared on their SocialLearn profile pages.

At an overall network level, learners can see in the general tagcloud all learning topics associated with the whole community. By clicking on a tag, learners filter the network and see only other learners who have an interest in that learning theme. By identifying topographically central people within the network, they can identify the most active people, as well as potential experts in the field. So learners can use the NAT plug-in as a Social Learning Browser to locate people who are dealing with the same learning topics. This is based on the logic of social recommender systems, but most recommender systems are based on people you may know through other connections, rather than the thematic content around which people form relations.

Social learning is often mediated via artifacts, and social capital can involve the exchanging of material resources. So both SocialLearn actors *and* artifacts are used as sources of tags, examples of artifacts being *Questions* posted to the Q&A site, and *Steps* on a learning *Path*. For our analysis, tags on artifacts that mediated associations between actors were added to the actors themselves. For example, if Actor A posted a *Thought* (analogous to a status update) with Tag T, and Actor B commented on that Thought, then Tag T would also be associated with Actor B. In this way we are able to visualize the flow of topics between actors.

Because people learn through an active social process of meaning construction [34], it is necessary to take the content of the interactions into account. The kind of information that is exchanged may influence the nature of the learning tie. While most social networking sites focus on finding people with a certain expertise, the NAT plug-in also focuses on finding people with the same learning topic and learning problem.

## 4.3 Multiplexity of Learning Ties

Engaging in networked learning means that learners need to be in touch with others in their network and need to build the networked connections that are required to participate in constructive conversations [4]. However, this is not easy because networked learning is a complex process situated in a changing context. It is difficult to pare this process down to one or two variables. A learning relation is a multiplex set of relations all acting at the same time.

In many analyses of social networks, ties between actors are differentiated only in terms of their relative strength. The SocialLearn platform supports a wide variety of actions that can result in the creation of ties between actors. Here we describe *responding* ties, *follower* ties and *friendship* ties (which as explained, can be further contextualized through the use of tags).

Actions that can result in interaction ties between actors include *responding* to materials contributed by another actor (typically through commenting on or replying to postings). Thus, if Actor B comments on a posting by Actor A there would be a ‘respond’ type tie from Actor B to Actor A.

Ties can be used to describe relations between actors in SocialLearn. Two types of actions were used to generate relations: *friending* (i.e. identifying another actor as someone who is a colleague, acquaintance or friend) and *following* (i.e. identifying that you want to be notified of the activities of another actor). Both these actions serve to indicate that one actor is in some way interested in another actor. Relations are directional and potentially non-symmetric (e.g. Actor A can identify Actor B as a ‘friend’ without Actor B identifying Actor A as a ‘friend’).

We found it important to include these friend and follower learning relationships because learning can be supported if relations between students in the network are characterized by trust, openness and confidence [35]. According to Argyris and Schön [36], trust and openness in social relations make it possible to test theories, experiences and practices. Borgatti and Cross [37] found that students are most likely to seek information from work-related experts who they believe will not make them feel uncomfortable. Figure 2 shows how the network visualization can be filtered and thus redrawn by combining different ties.

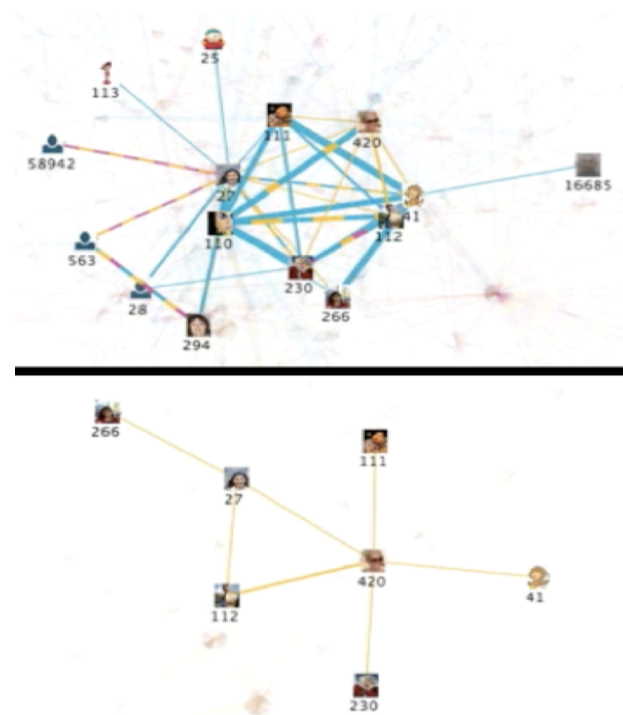
## 5. SUMMARY AND FUTURE WORK

To summarise, we have presented our Networked Learning theoretical perspective, and described a demonstrator which begins to show how this can be translated into a Social Learning Analytics tool. The NAT plug-in for SocialLearn *visualizes networks by identifying relationships between people who interact around the same learning topics*. From an ego-perspective learners can see their own learning network, consisting of their friends, followers and other learners with whom they have interacted. This means that the NAT plug-in has the potential to provoke learning-centric reflection by learners on how they use their peers for learning. Learners can also see the content of the ties, summarized in one or more tags.

Educators can use the plug-in to guide students in the development of networked learning competences and to gain insight into the ability of groups of students to learn collectively over time. Using this plug-in, educators can detect multiple (isolated) networks within the online learning environment, connect ideas and foster collaboration beyond existing boundaries.

The visualizations and network data can be used to carry out social network analysis of the density of a network, including the centrality of persons within a network, the structure, cliques, etc, in real time or over a specified period. For researchers, the analysis of learning ties and networks helps clarify how professionals engage in learning relationships, as well as the value of this engagement.

This work is at an early stage. We have completed one iteration to put the representational infrastructure in place, which now opens up many possible lines of enquiry. More research is needed to



**Figure 2: A subnetwork already filtered by topic. Actors may be connected by any combination of the ties *friend* / *follow* / *respond*, reflected in the combination of colours on the links (top). Link thickness reflects quantitative strength (e.g. many blue *responses* between actors). Filtering on just *friend* ties (lower) refreshes the network layout, revealing a different structure in which actors may become more central/peripheral.**

investigate which sets of ties can predict or stimulate learning. It may prove possible to apply the theory of Borgatti and Cross [37] to an online learning environment and to investigate whether people who are friends are more likely to seek information from each other.

We have not yet analysed whether different ties yield systematically different structures. Qualitative research is needed to interview actors about their perceptions of their learning networks, their (and mentors’) reactions to these visualizations. What do learners themselves perceive as the best types of learning tie? Does the content of ties influence the structure of the learning network of which it forms a part, and does it help us track the flow of social capital within a network?

We plan to develop the NAT plug-in further in order to make it possible to conduct temporal SNA in order to study network dynamics. A ‘replay’ tool should help see the growth of the overall network and changes in the networked learning behaviour of individual students. Do students find more peers to learn from using the NAT plug-in?

## 6. ACKNOWLEDGEMENTS

We gratefully acknowledge The Open University for making this work possible through a SocialLearn Project Internship awarded to the first author.



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